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Hybrid model for detection of brain tumor using convolution neural networks

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ABSTRACT

The development of aberrant brain cells, some of which may turn cancerous, is known as a brain tumor. Magnetic resonance imaging (MRI) scans are the most common technique for finding brain tumors. Information about the aberrant tissue growth in the brain is discernible from the MRI scans. In numerous research papers, machine learning, and deep learning algorithms are used to detect brain tumors. It takes extremely little time to forecast a brain tumor when these algorithms are applied to MRI pictures, and better accuracy makes it easier to treat patients. The radiologist can make speedy decisions because of this forecast. The proposed work creates a hybrid convolution neural networks (CNN) model using CNN for feature extraction and logistic regression (LR). The pre-trained model visual geometry group 16 (VGG16) is used for the extraction of features. To reduce the complexity and parameters to train we eliminated the last eight layers of VGG16. From this transformed model the features are extracted in the form of a vector array. These features fed into different machine learning classifiers like support vector machine (SVM), naïve bayes (NB), LR, extreme gradient boosting (XGBoost), AdaBoost, and random forest for training and testing. The performance of different classifiers is compared. The CNN-LR hybrid combination outperformed the remaining classifiers. The evaluation measures such as recall, precision, F1-score, and accuracy of the proposed CNN-LR model are 94%, 94%, 94%, and 91% respectively.

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1. INTRODUCTION

The brain is a vital organ of the human body responsible for control and decision-making. As the control center of the nervous system, this part is very important to protect against injury and disease. Brain tumors are one of the life-threatening diseases that directly affect a person's life. Delineating the cranial layers surrounding the brain makes its behavior difficult to study and also increases the complexity of disease detection [1]. Brain diseases are not the same as other parts of the body, but they can be caused by abnormal growth of cells that eventually destroy the structure of the brain and cause brain tumors. However, the World Health Organization (WHO) reports an estimated 9.6 million people died of cancer worldwide in 2018 and

about 30% to 50% of patients diagnosed with primary cancer [2]. Among many types of cancer, brain tumors are deadly cancers. Thus, according to statistics, about 17,760 adults died from brain tumors in recent years. Due to the disastrous location and abnormal growth of cancer, as well as the complexity of brain structures, timely diagnosis is necessary. Many medical imaging methods have been developed to acquire images for the diagnosis of different diseases. Ultrasonic imaging (UI), computed tomography (CT), X-ray, single-photon emission computed tomography (SPECT), magnetic resonance spectroscopy (MRS), positron emission tomography (PET), and MRI are commonly employed technologies [3]. Magnetic resonance imaging (MRI) is very useful for tumor analysis with high-quality brain imaging. MRI technology has become more important in brain imaging [4] because MRI technology offers a unique opportunity to obtain the best possible visualization of maximum spatial and contrast determination.

A correct understanding of brain tumor staging is an important issue for disease prevention and treatment. To this end, MRI is widely used by radiologists to analyze brain tumors [5]. The results of this analysis indicate whether the brain is normal or abnormal. On the other hand, if an abnormality occurs, it identifies the tumor type. With the advent of machine learning, it becomes increasingly important to process MRI for rapid and accurate brain tumor detection [6]. Initially, the study consisted of three parts: (i) pre-processing of MR images; (ii) feature generation and extraction; and (iii) classification. Several automated or semi-automated methods have been proposed in recent years for the diagnosis and classification of brain tumors [7]. Gray-level co-occurrence matrices (GLCM) are commonly used for low-level feature extraction [8]. Neural networks (NN), on the other hand, are used for classification problems dealing with the complex textures of brain tumors. Deep learning (DL) was introduced to model new complex and nonlinear relationships between input and output layers [9]. DL structures are an extension of traditional NNs. It is formed by adding an additional hidden layer to the network model. In machine learning, we use DL as subfields to describe feature hierarchies [10]. This subfield builds on the demonstration of multiple levels of learning. Higher levels are defined by lower levels and help explain many of the higher levels. The higher level has the same functionality as the lower level. DL has attracted researchers' interest due to its excellent performance and is the best solution for many problems in the analysis of medical image applications such as image denoising, segmentation, and classification [11]. It has been proven that various DL architectures currently exist, but in recent years, convolution neural networks (CNN) have been used as an architecture that uses convolutional filters to perform complex operations [12]. To classify images, CNN is a network architecture commonly used along with some of the machine learning classifiers.

Ural [13] proposed a method that leverages a probabilistic neural network (PNN) approach for the detection and localization of brain tumors. Notably, their proposed method achieves a low computational time while maintaining a reasonably high level of accuracy [13]. Classification involved the utilization of two NN architectures: fully connected networks and CNN. Within these two architectural categories, additional experiments were conducted by augmenting the original 512×512 axial images [14]. Research by Kang *et al.* [15] states that combining deep features in an ensemble leads to a significant performance improvement. In the majority of cases, the support vector machine (SVM) with a radial basis function (RBF) kernel outperforms other machine learning classifiers [15]. Rammurthy and Mahesh [16] proposed a brain tumors detection method, called "whale Harris Hawks optimization" (WHHO), which combines the whale optimization algorithm (WOA) and Harris Hawks optimization (HHO) within a DL framework. It begins with image tumor segmentation using cellular automata and features such as size, variance, mean, and kurtosis are extracted. These features are then used for enhanced brain tumor detection through the WHHO approach [16].

Sharif *et al.* [5] presented active DL system for brain tumor segmentation and classification. The process involved contrast enhancement, followed by the saliency-based deep learning (SbDL) method to create a saliency map. Thresholding was applied, and the resulting images fine-tuned a pre-trained CNN model, inception V3. Additionally, dominant rotated local binary pattern (DRLBP) features were extracted and combined with CNN features [5]. The study evaluated the performance of tumor classification methods for categorizing MR brain image features into distinct classes, including "n/a," "multifocal," "multicentric," and "gliomatosis." This classification process involved the analysis of statistical properties within the input images and the systematic categorization of the data into different groups [17]. Ge *et al.* [18] proposed an approach involved generative adversarial network (GAN)-based augmentation of brain MRI to enhance the training dataset. It used post-processing to combine glioma subtype classifications at the slice level via majority voting. A two-stage training strategy was employed, starting with GAN-augmented MRIs and transitioning to real MRIs for learning glioma features [18]. Summary of few proposed methods listed in the Table 1.

These methods use a variety of techniques and algorithms to enhance the accuracy of brain tumor detection and classification, combining DL, feature extraction, ensemble methods, and data augmentation to improve the performance of the systems. The choice of methods and techniques may vary depending on the specific objectives and available data. Each method mentioned has its own limitations. For example, the

performance of SVM with RBF kernels can be sensitive to hyperparameter tuning, and the effectiveness of optimization algorithms like WOA and HHO can depend on the specific problem and dataset. Addressing these weaknesses often requires careful consideration of the specific application, data, and clinical context, as well as ongoing research and development to improve the robustness and reliability of these methods in clinical practice.

Table 1. Summary of related work

Author	Classification Method	Dataset	Accuracy (%)
Ural [13]	PNN	25 MR images	90
Albawi *et al.* [19]	CNN	587 MR images	91.16
Paul *et al.* [14]	Fully connected and CNN	3064 MR images	91.43
Kang *et al.* [15]	SVM, RBF	253,2364	89
Rammurthy and Mahesh [16]	WHHO	BraTS	81.6
Sharif *et al.* [5]	SbDL	BraTS17	83.73
Cinarer and Emiroglu [17]	SVM, KNN	Kaggle	90
Ge *et al.* [18]	U-Net architecture, GANs	BraTS	88.82

In this paper, gigantic non-handcrafted highlights are extricated utilizing CNN to demonstrate at that point different classifiers are considered to classify the course of the given MRI brain pictures. The CNN- logistic regression (LR) demonstrates employment points of interest in both strategies. The focal points of CNN are scanty networks among the neurons between progressive layers and weight sharing between layers. The LR classifies the information tests based on the subordinate highlights we have given. This CNN-LR demonstrates extricated the notable highlights consequently and diminishes the difficulty and time utilization. Consequently, this proposed demonstration has way better execution compared to other models CNN-SVM [20], CNN-XBoost, CNN-Adaboost, CNN-decision tree, CNN-voting classifiers, CNN-K-nearest neighbor (KNN), CNN-random timberland, CNN-naive bayes (NB). Performance metrics: in this paper, the proposed CNN-LR show is assessed based on execution measurements such as precision, F1-score, accuracy, and recall. These execution measurements are characterized as takes after.

$$Accuracy = correct\_preds/all\_preds$$

$$Precision = true\ positive/(true\ positive + false\ positive)$$

$$Recall = true\ positive/(true\ positive + false\ negative)$$

$$F1 = 2 \times\ (precision\ *\ recall)/\ (precision\ +\ recall)$$

2. METHOD

2.1. Transfer learning

Transfer learning empowers us to use the data learned by a pre-trained demonstrate to improve execution on a modern, related assignment, as opposed to starting from zero and preparing an unused demonstrate from scratch on an unused dataset. This regularly produces prevalent comes about whereas sparing a critical sum of time and computational assets [21]. For occasion, a pre-trained picture acknowledgment show that was created on a sizable dataset like ImageNet can be moved forward on a smaller dataset for a specific work, like identifying different sorts of objects. By beginning with a pre-trained show. In this paper we utilized a pre-trained demonstration visual geometry group 16 (VGG16) for include extraction [22], we'll not make utilize of the completely associated range of VGG16 since, in this work, classification is done utilizing machine learning algorithms like SVM [23], NB, LR, extreme gradient boosting (XGBoost), AdaBoost, and random forest. The layers of VGG16 are reduced to decrease m the complexity. The layers in the reduced model consist of 3 blocks. In the first block, there will input layer in which the size of the image is (32,32,3), it is followed by two convolutional layers and max-pooling layers of the following size (conv1(32,32,64), conv2(32,32,64), max(16,16,64)). The block2 the input size goes through the following changes, the layers will be the same as block1(conv1(16,16,128), conv1(16,16,128), max(8,8,128)) as given in the Figure 1. In the last block, we have three convolutional layers and one max pooling layers in which image size goes through changes (conv1(8,8,256), conv2(8,8,256), conv3(8,8,256), max(4,4,256). At last, we have added the flattened layer.

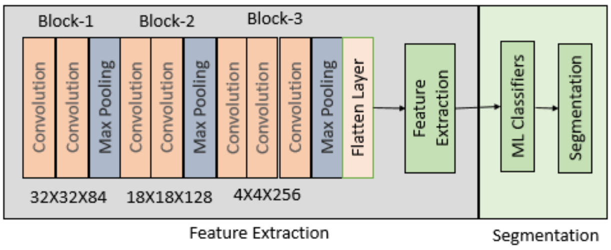

Figure 1. Block diagram of the model

2.2. Logistic regression as classifier

CNN performance as a classifier is affected by the overfitting phenomenon. Since the CNN model is complex, the effect of excessive assembly will take effect when training available data is limited [24]. In a way to improve performance, we propose the use of LR on CNN features. LR could be a factual strategy commonly utilized in machine learning for binary classification issues, where the objective is to predict one of two conceivable results, such as true/false or yes/no. Here are a few reasons why LR is widely used in classification assignments. LR may be a moderately basic calculation that's simple to get it and translate [25]. It can give insights into the relationship between the independent factors and the likelihood of a specific result. LR can perform well indeed when there's constrained information accessible, making it a valuable calculation when managing with little datasets. In general, LR may be a well-known and compelling strategy for twofold classification issues. Be that as it may, it may not be reasonable for more complex classification issues where there are different classes or nonlinear connections between the input factors and the result.

3. EXPERIMENTAL SETUP

The MRI in the dataset is of distinctive measure so these pictures are resized to the size (32×32). These pictures are put away in an array and there comparing labels in another array. The indexes are utilized to coordinate the picture with the comparing label. The part proportion of 9:1 is utilized, which implies 90% of information is utilized in the training phase and 10 % is utilized in the testing phase. The first thing we import here is the VGG16 model in tensorflow keras. The preprocess _input module is imported to properly scale pixel values for the VGG16 model. Image modules are imported to preprocess image objects. The numpy module is imported for array processing. Then the pre-trained weights of the imagenet dataset are loaded into his VGG16 model. A VGG16 model consists of convolutional layers followed by one or several fully connected dense layers [22]. We can choose if required the final dense layer using include _top. A value of false indicates that the final dense layer has not been loaded into the model. Since the feature extraction component of the model extends from the input layer to the final max pooling layer, we used three blocks of convolutional layers followed by max pooling. Finally, a flattened layer to collect the features in an array format as given in the Figure 2. Different machine learning classifiers are applied and chosen LR based on its performance, so the softmax layer of the fully connected layer is removed in VGG16.

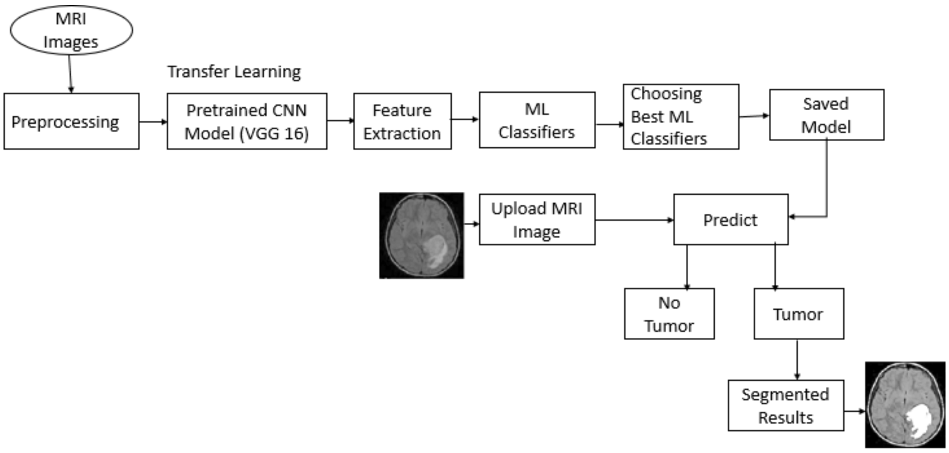

Figure 2. Testing and training phases

4. RESULTS AND DISCUSSION

The evolution of the proposed model is performed on the image database of brain tumors from Kaggle and executed on a Dell laptop with intel i5, 12th generation processor, 16 GB DDR4 RAM, and 4 GB NVIDIA graphics card. The dataset consists of 253 images total of which 98 images are of no class and 155 images are of yes class as given in Table 2. The authors of the dataset are A. Kang, Z. Ullah, and Jeonghw. In pre-processing, the training data set and testing data set both are processed in the required format, image augmentation is applied and then used for the training phase and testing phase. Each image size is 32×32×3. The CNN model is trained to a training data set of 253 images of 98 no-tumor images and 155 tumor images.

Table 2. Data set

S.No.	Tumor class	No. of images
1	Tumor	155
2	No-tumor	98

The architecture of the CNN model is described in CNN model architecture and shown in Figure 1. The complete training process is shown in Figure 2. The CNN will extract the features of every image, these features and corresponding labels are given to the machine learning classifiers for testing and training. The accuracy of all machine learning classifiers tested is given in Figure 3. The confusion matrix for every algorithm is obtained and compared to the algorithm with the most accuracy is considered as our model, i.e. CNN-LR. The performance metrics of different algorithms are listed in Table 3.

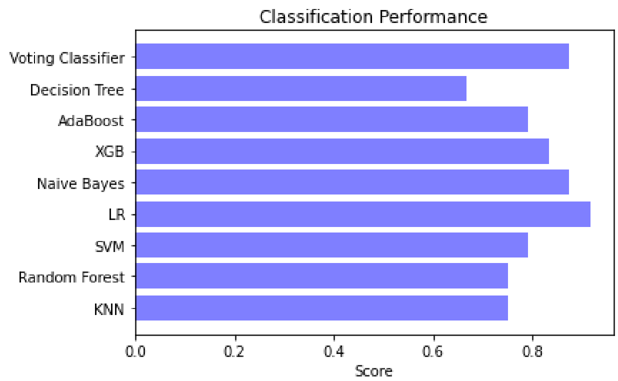

Figure 3. Accuracy comparison

Table 3. The performance metrics of different algorithms

S.No.	Method	Recall	Precision	F1Score	Accuracy
1	CNN-KNN	81	81	81	75
2	CNN-random forest	78	88	82	75
3	**CNN-LR**	**94**	**94**	**94**	**91.66**
4	CNN-SVM	82	88	85	79.16
5	CNN-NB	88	94	91	87.5
6	CNN-XGBoost	83	94	88	83.33
7	CNN-AdaBoost	79	94	86	79.16
8	CNN-decision tree	75	75	75	66.66
9	Voting classifier	88	94	91	87.5

Along with the accuracy recall, precision, and F1-scores are also calculated for all the machine learning classifiers. While accuracy is a straightforward metric, the F1-score and other metrics are often preferred when dealing with imbalanced datasets or when certain classes are of greater importance, especially in medical imaging. It's essential to consider the specific problem and data distribution to choose the most appropriate evaluation metric. In our implementation, precision-recall and F1-scores metrics of CNN-LR are outperformed when compared with the remaining classifiers.

5. CONCLUSION

In this study, a hybrid CNN-LR model is taken into account for the MRI brain tumor classification problem by training the model using the brain tumour dataset. In order to forecast the output class, non-handcrafted features are retrieved by CNN and applied as input to a variety of classifiers, including KNN, CNN, SVM, LR, NB, voting classifiers, XGBoost, Adaboost, and decision tree. Performance criteria including accuracy, F1-score, precision, and recall are used to assess the effectiveness and viability of the proposed hybrid CNN-LR model. The findings demonstrate the benefits of this model combination. According to the findings, this hybrid CNN-LR model is a viable model for classifying MRI brain tumors. In contrast to previous traditional classifiers, which took more time to extract the appropriate hand-crafted features, the model automatically extracted the relevant characteristics, reducing the tedious and time-consuming process. Second, this hybrid CNN-LR model integrated the best aspects of the two most effective and widely used classifiers for image recognition and classification, CNN and LR. Finally, the decision-making process slightly increases the complexity of the hybrid model. The suggested CNN-LR model outperformed all other models, including CNN-Xgboost, CNN-SVM, CNN-NB, CNN-voting classifier, and CNN-decision tree, with an accuracy of 91.66%. The main limitation of the work is dataset class imbalances and limited dataset size. These issues need to be addressed in future work along with state of art CNN architecture-based transfer learning needs to adopt to enhance the model's performance.

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